POINT ESTIMATE METHOD BASED UNCERTAINTY MODELLING FOR DISTRIBUTED GENERATION ALLOCATION USING DIFFERENTIAL EVOLUTIONARY ALGORITHM

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology
In
Electrical Engineering

(Power Electronics and Drives)

By

Chaduvula Hemanth

Roll No: 213EE4322

Department of Electrical Engineering

National Institute of Technology, Rourkela

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Under the guidance of

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CERTIFICATE

*I hereby certify that the work which is being presented in the thesis entitled "**Point estimate method based uncertainty modeling for distributed generation allocation using differential evolutionary algorithm**" in partial fulfillment of the requirements for the award of **Master of Technology** degree in **Electrical Engineering** submitted in Electrical Engineering department of National Institute of Technology, Rourkela is an authentic record of my own work carried out under the supervision of Dr.Sanjib Ganguly, Assistant professor, Department of Electrical Engineering.*

The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

(Chaduvula Hemanth)

This is to certify that the above statement made by candidate is correct and true to best of my knowledge.

(Dr. Sanjib Ganguly)
Department of Electrical Engineering
National Institute of Technology, Rourkela
Rourkela -769008

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Chaduvula Hemanth

Dedicated to
My loving Parents and
My sister

ABSTRACT

Now a day's distributed generation plays an important role in distribution network for energy and environmental challenges. The placement of distributed generators is significantly effects the distribution network operation. The optimal accommodation of distributed generators provide maximum benefits in terms of voltage profile, power losses, power quality, reliability etc. The scope of this study considers determination of optimal locations and capacities of DG in uncertain conditions along with satisfaction of constraints. The uncertainties are due to stochastic wind speed, variable solar irradiation, uncertain fuel price, random load growth and electricity price. The constraints include voltage, thermal and penetration level of DG. Point estimate method (PEM) is used to solve the Probabilistic power flow (PPF) model which efficiently considers the uncertainties involved in the generations and loads. The multi objective function consider the minimization of costs include investment cost, cost of maintenance, operating cost, network loss cost and cost of purchased energy. The Differential evolutionary algorithm (DEA) with embedded PEM is applied as a new methodology to determine the optimal locations and capacities of DG. The proposed DEA-PEM technique is applied on IEEE 33-bus and 69-bus systems respectively. The results shown that cost of distributed network with DG is less compared to without DG for a duration of 25 year planning period.

CONTENTS

LIST OF SYMBOLS

P_{DG}^{N}	installed capacity of distributed generation
P_i	active power injection at bus i
Q_i	reactive power injection at bus i
P_{DG}	active power output of DG
Q_{DG}	reactive power output of DG
P_L	total load of distribution system
W_{loss}	energy loss
N_{DG}	candidate bus for installing DG
N_{type}	type of DG
V_i	voltage at bus
S_{ij}	feeder power plow in line
C^I	investment cost
C^M	maintenance cost
C^{Lt}	network loss cost
C^O	operating cost
C^P	cost of energy purchased from grid
T^M	maintenance hours
T^O	operating hours
P_{wT_n}	nominal wind power output
P_{s_n}	nominal solar power output
v	wind velocity
s	solar illumination intensity

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

The definition of Distributed Generation can't be concluded strict to the following terms such as purpose, location, rating of distributed generation, power delivery area, technology, environmental impact, and the mode of operation, ownership and the penetration of distributed generation. Distributed Generation is an electric power source connected directly to the distribution network or on the customer site of the meter. In literature, a number of terms such as 'embedded generation', 'dispersed generation', and 'decentralized generation' are used in place of distributed generation. DG technologies are categorized into renewable and fossil fuel-based sources. Now a day's renewable energy sources (wind, solar, biogas, biomass, geothermal, etc.) are used because of reduction in carbon emission and energy saving. The distributed generation is classified into micro generation in the range of (1W-5kW), small generation in the range of (5kW-5MW), medium generation in the range of (5MW-50MW) and large generation in the range of (50MW-300MW) [1]. The optimal distributed generation allocation in distribution network is a challenging issue for better network operation. The operation of distribution network is affected by placement of DG. An Optimal DG allocation provides an improvement in voltage profile, reduction in network losses, power quality improvement and reliability of supply while considering the constraints imposed by network, DG operation and investment constraints. On the other hand, an inappropriate allocation causing negative impacts such as network instability, voltage rise, reverse power flows, increasing line losses, raise in carbon emissions in case of fuel based DG and poor reliability in case of renewable type of DG such as wind and solar.

The various state-of-the art techniques and methods are proposed to address the DG integration in distribution network [2]. These methods differ according to formulation of problem and solving strategy. In analytical analysis, demand-generation snapshot scenario is considered for the minimization of power losses as the objective. This method will not consider other generation and load scenarios. Due to that, technical issues such as voltage and thermal constraints will not accounted in this analysis. In addition to that, sequential procedure is required for the operation of multiple DG plants which results in sterilization of capacity [3]. In exhaustive analysis, multiple objectives such as energy losses, voltage rise, short-circuit levels, economic and environmental issues are considered. This analysis is computationally burden when multiple DG connections are considered [4]. Linear programming is a robust optimization method, which consider different issues such as minimization of curtailment cost, maximization of DG capacity, maximization of wind energy and optimal curtailment allocation [5]. The ac Optimal Power Flow (OPF) is a non-linear programming problem, uses multi periods for considering the variability in generations and loads. This model considers the objectives such as power losses, maximization of DG capacity and minimization of energy losses [6-7]. Metaheuristic algorithms are iterative based and they require tuning of parameters for best solution [8-11]. Even though many techniques are available for DG integration, barrier to implementation of these techniques are due to its complexity and problem formulation.

The uncertainties related to DG are its variable nature and unavailability of the unit when it is required to generate. It is great challenge to determine the optimal locations and capacities of DG under uncertain conditions. The approaches such as fuzzy based and probabilistic based are used to model the uncertainty. Fuzzy based approach express the uncertainties in generations and loads as fuzzy numbers [11]. Probabilistic Power Flow (PPF), which considers many generations and loads to address this issue. PPF model, is one of best approach for Optimal DG Placement (ODGP) problem. The probabilistic approaches require large amount of data to address the problem. The bench mark method known as monte carlo simulation (MCS) method provides accurate results. However, Point estimate method will give identical results as that of MCS with less computational burden for solving PPF model. The optimal DG allocation is solved by using GA-MCS approach in [34]. In [35], GA-PEM method is proposed for optimal distributed generation placement. This paper considers PEM embedded Differential evolutionary algorithm (DEA) for finding the best locations and capacities of distributed generation.

1.1 Literature Review

In addition to locations and capacities; the DG technology also affects the operation and planning of distribution network. The optimal allocation of DG provides best locations and capacities for better planning and operating strategy for network. Most of the methods for optimal locations and capacities of DGs are deterministic based. These methods cannot consider a sufficient range of scenarios to address real problem. Few techniques consider time dependenency of load and generation. The various DG connection methodologies include cost-effective connections in liberalized countries, efficient generation technologies and operational perspective. The various solving strategies and methods are developed for optimal DG connections in [2]. Distributed Generation developers will seek to connect as much capacity as possible with limited number of units where as Distributed network operators look for deferral of network reinforcement and network loss costs. Here, Tradeoff analysis technique is used to solve the multi objective optimal power flow problem to incentivize both the parties [12].

Multi-objective planning methods consider in all aspects of technical, environmental and economic impacts of DG integration. DG planning objectives are naturally conflicting. A multi objective planning problem has set of solutions rather than single solution because of conflicting objectives. These set of solutions known as pareto set, in which all objectives optimized simultaneously in [13]. The percentage of losses is related to capacity of DG and various categories of demand-generation scenarios in [14]. The optimal accommodation of distributed generation in MV distribution networks using genetic algorithm is to consider voltage profile, feeder capacity and three-phase short circuit level in the network nodes [15]. Most of the multi objective methods for optimal accommodation of DGs include minimization of energy loss, network upgrade, evaluation of multi objective performance index (performance indices such as feeder capacity, short circuit level and voltage deviation etc.), minimization of curtailment and dispatch of units and cost minimization [14,16-18].The analytical approaches are advantageous in reducing the computational effort but require more assumptions and complicated mathematical computations [3].

The optimal placement of distributed generation in distribution network using Non-sorting genetic algorithm-II (NSGA-II) will provide technical, economical and environmental benefits by considering the special requirements such as power quality and power supply [19].

Minimizing the negative impacts of voltage rise and transmission system voltages through enhanced utilization of distributed generation with fixed power factor setting and tap setting of on load tap changing transformer [20]. In [21], the facility of increased generator connections is provided by active power flow management in which operating margin as an element. The analysis of network under variable renewable generation and loads in optimal power flow (OPF) problem along with satisfaction of constraints is presented in [22]. The network losses are dependent on DG penetration level and DG technologies used. The losses follow the U-shaped trajectory with DG penetration level. The wind technology shows worst behavior in case of loss reduction [23]. The interconnection of distributed generation in distribution networks consider network reconfiguration, rewiring and switchgear requirement etc. in [24]. The optimal allocation of distributed generation using differential evolutionary algorithm (DEA) considers minimization of cost of energy purchased from grid, cost of network losses and cost of network upgrading along with technical and economical benefits [25].

The Backward/Forward load flow approach for solving the load flow problem in radial distribution network based on KCL and KVL equations is presented in [26]. The modeling of wind and solar generators are presented in [27-28]. In [29-32], point estimate method is proposed for solving the probabilistic power flow problem. The concept of differential evolutionary algorithm and its strategies proposed in [33]. The optimal distributed generation allocation under uncertainties using GA-MCS approach in [34]. In [35], optimal distributed generation allocation under uncertainties using GA-PEM technique.

1.3 Organization of report

The report is organized as follows: The mathematical modeling of objective function and constraints are given in chapter 2. The uncertainties such as wind power, solar power, load growth, fuel price and electricity price are modeled. Backward/Forward sweep load flow method and point estimate method (PEM) are described in chapter 3. The concepts of differential evolutionary algorithm (DEA) and its applications are outlined in chapter 4. In chapter 5, the proposed DEA-PEM approach is applied on IEEE 33 bus and 69 bus systems respectively. The simulation results and discussions are drawn in chapter 6. Finally in chapter 7, conclusions and future work is mentioned.

CHAPTER 2

MATHEMATICAL MODELING OF OBJECTIVE FUNCTION

2.1 Objective Function

An optimal DG allocation provides the minimization of costs associated with distributed generation and distributed network. These costs include DG investment cost, DG maintenance cost, DG operation costs, energy loss cost and cost of energy purchased from grid. The operating cost in case of renewable generation is zero.

$$\min f = b_1 C^I + b_2 C^M + b_3 C^O + b_4 C^{Lt} + b_5 C^P \tag{2.1}$$

$$\min\ f = b_1 \sum_{k=1}^{N_{type}} \sum_{i \in N_{DGk}} C^I P^N_{DGki} + b_2 \sum_{k=1}^{Ntype} \sum_{i \in N_{DGk}} (C^M_{DGk} T^M_{DGki} P^N_{DGki})$$

$$b_3 \sum_{k=1}^{Ntype} \sum_{i \in N_{DGk}} (C^O_{DGk} T^O_{DGki} P^N_{DGki}) + b_4 C^L W_{loss} +$$

$$b_5 C^L ((T * \overline{P_L}) - \sum_{k=1}^{Ntype} \sum_{i \in N_{DGk}} (T^O{}_{DGki} P^N_{DGki}))$$

where b_1, b_2, b_3, b_4 , b_5 are the weighting coefficients: $b_1 + b_2 + b_3 + b_4 + b_5 = 1$. C^I_{DGk}, C^M_{DGk} and C^O_{DGk} are the investment, maintenance and operating cost of the k_{th} type of DG.

P^N_{DGki} is the rating of the k_{th} type of DG at bus i

$\overline{P_L}$ = (Load factor)* P_L

P_L is total load of the distribution system

N_{type} is the number of different DG technologies

N_{DGk} is the ocation for installation of k^{th} type of DG

T^M_{DGki}, T^O_{DGki} is the maintenance, operating hours of the k_{th} type of DG at bus i

T is the total hours in a planning period

2.2 Constraints modeling

2.2.1 Deterministic equality constraints

Backward/Forward sweep load flow method calculates the current flow in the feeder, voltage and angle of the bus by using following equations [26].

$$I_i = \left[\frac{((P_{Li} - P_{DGi}) + j(Q_{Li} - Q_{DGi}))}{V_i} \right]^*$$

$$I_{ij} = I_j + \sum \text{currents in branches emanating from node j} \tag{2.2}$$

$$V_i \underline{|\delta_{ij}} = V_j + I_{ij} * Z_{ij} \tag{2.3}$$

P_{Li} and Q_{Li} are the active and reactive load power at node i. P_{DGi} and Q_{DGi} are the active and reactive output power of the generators at node i. I_{ij} is the current in the feeder between node i and node j. Z_{ij} is the impedance between node i and node j. V_i is the voltage magnitude at node i. δ_{ij} is the voltage angle between bus i and bus j.

2.2.2 Deterministic inequality constraints

These constraints related to technical issues such as voltage, output power of generators, total and renewable DG penetration level. These constraints include the upper and lower limits of output active and reactive powers of DGs. The permitted installed capacity and penetration level of RES for carbon emission reduction is considered [35].

$$P_{DGi\min} \le P_{DGi} \le P_{DGi\max} \qquad (i=1,2,\ldots\ldots\ldots\ldots N_{DG}) \tag{2.4}$$

$$Q_{DGi\min} \le Q_{DGi} \le Q_{DGi\max} \qquad (i=1,2,\ldots\ldots\ldots\ldots N_{DG}) \tag{2.5}$$

$$\sum_{i=1}^{N_{DG}} P_{DGi}^{N} \le DG \text{ pen} \sum_{i=1}^{N_B} P_{Li} \tag{2.6}$$

$$\sum_{i=1}^{N_{RES}} P_{DGi}^{N} \ge RES \text{ pen} \sum_{i=1}^{N_{DG}} P_{DGi}^{N} \tag{2.7}$$

Where N_{DG} indicates number of installed DGs, N_B is the number of nodes of the distribution network, N_{RES} represents number of renewable energy sources, DGpen represents penetration of total distributed generators and RESpen represents penetration of renewable energy sources in distribution network.

The voltage limits at each node is given by

$$V_{i\min} \leq V_i \leq V_{i\max} \tag{2.8}$$

The feeder power flow is lower than maximum value

$$S_{ij} - S_{\max} \leq 0 \qquad ij = 1,2,\ldots\ldots\ldots\ldots\ldots\ldots\ N_B \tag{2.9}$$

2.3 Mathematical model

The optimal allocation of the DGs can be mathematically formulated as

$$\begin{aligned} &\min\ \{f(E,\zeta)\} \\ &s.t.\ f(E,\zeta) \leq \overline{f} \\ &\quad \mathrm{G}=0 \\ &\quad \mathrm{H}_{\min} \leq H \leq H_{\max} \end{aligned} \tag{2.10}$$

where E represents the solution vector, ζ indicates set of random variables. $f(E,\zeta)$ is the objective function, $\overline{f}$ is the value of the objective function without penalty . $G=0$ represents equality constraints and $H_{\min} \leq H \leq H_{\max}$ represents inequality constraints.

CHAPTER 3

MODELING OF THE UNCERTAINTIES and PEM TO SOLVE THE PPF MODEL

3.1 Modeling of Uncertainties

3.1.1 Output power of wind generating unit

The variable nature of wind speed follows the weibull probability distribution function according to survey. The probability density function of wind speed is given by

$$f(v) = \frac{k}{c^k} v^{k-1} \exp(-(\frac{v}{c})^k) \qquad 0 \le v \prec \infty \tag{3.1}$$

where v is the wind velocity in m/sec is random in nature. k and c represents the shape and scale parameters of the weibull distribution curve [27].

$$P_{WT} = \begin{cases} 0, & \text{if } 0 \le v \le v_{ci} \\ P_{wT\_n} \dfrac{(v - v_{ci})}{(v_n - v_{ci})}, & \text{if } v_{ci} \prec v \le v_n \\ P_{wT-n}, & \text{if } v_n \prec v \prec v_{co} \\ 0, & \text{if } v_{co} \succ v \end{cases} \tag{3.2}$$

v_{ci} and v_{co} are the cut-in and cut-out wind speed, v_n is the rated speed of wind turbine and P_{wT_n} is the rated wind turbine output power. Fig.1 shows the relation between wind power output and wind speed.

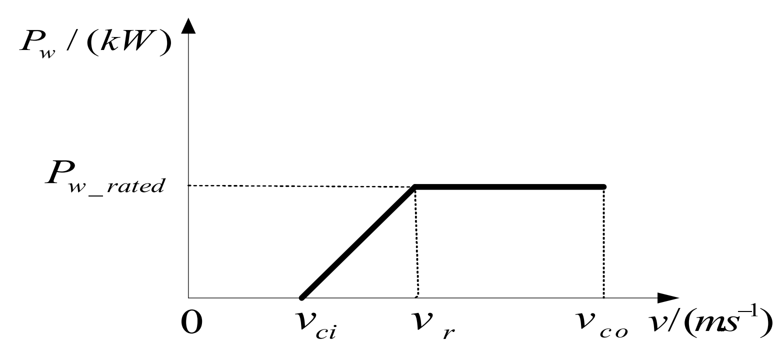


Fig. 3.1 Relationship between wind turbine output power and wind speed

3.1.2 Output power of photovoltaic's

Solar irradiation also follows weibull distribution based on historical and meteorological data in each region. The probability density function of solar irradiation is given by

$$f(s) = \frac{k_s}{c_s^{k_s}} s^{k_s - 1} \exp\left(-\left(\frac{s}{c_s}\right)^{k_s}\right) \qquad 0 \le s \prec \infty \tag{3.3}$$

Where s is the solar illumination intensity. k_s and c_s represents shape and scale parameters. The output power of a photovoltaic panel and the solar irradiation are related as [28]

$$P_s = \begin{cases} P_{s\_n} \dfrac{s}{s_n}, & 0 \le s \prec s_n \\ P_{s\_n}, & s_n \ge s \end{cases} \tag{3.4}$$

Where s is the solar illumination intensity, s_n is the rated illumination intensity of the photovoltaic panel and P_{s_n} is the rated output power of the photovoltaic panel. Fig 2 shows the curve between PV panel output power and solar irradiation.

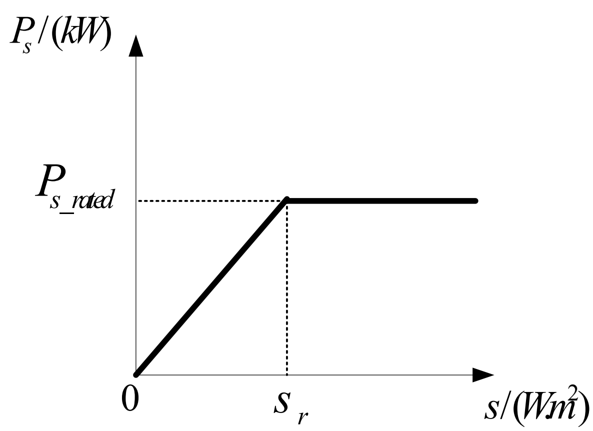


Fig. 3.2 Relationship between the photovoltaic panel output power and solar irradiation

3.1.3 Uncertain load growth

Due to increase in electricity demand, the load growth takes place at every node in the network. It is difficult to predict the load growth in coming years. The load growth of bus i at year t, $\Delta P_{Li}(t)$, follows the normal distribution with mean $\mu_i(t)$ and standard deviation $\sigma_i(t)$.

3.1.4 Uncertain fuel prices:

The operating cost of fueled generators involves mainly fuel cost. The cost of fuel continues to fluctuate throughout the year. The fuel cost is dependent on cost of crude oil, refining units, local market conditions, geopolitical factors, subsidies, taxation and therefore it is difficult to forecast the volatile fuel price. Inflation adjusted net present value technique is adopted to predict the fuel price .

$$p_f(t) = p_f(t-1) * \frac{(1+i)^t}{(1+\eta)^t} \tag{3.5}$$

Where $p_f(t)$ is the price of fuel in year t; $p_f(t-1)$ is the price of fuel in previous year; i and η are the inflation rate and discount rate respectively.

3.1.5 Uncertain electricity price

The electricity price is influenced by the government policy, location and range of units consumed. The electricity price generated on a yearly basis.

3.2 Backward/Forward Sweep Load Flow Algorithm

The load flow analysis is conducted for the evaluation of power system under steady state operating conditions. Backward/Forward sweep load flow algorithm is efficient for radial distribution network, due to its special features like low X/R ratio and unbalanced load.

In this approach, initially all bus voltages are assumed as 1p.u. In backward sweep using Kirchhoff's voltage law (KVL), all nodal currents are calculated and then branch currents are calculated using Kirchhoff's current law (KCL). Using these branch currents, the voltages toward the source node calculated. In forward sweep, with these updated voltages nodal currents are determined. The process continues till difference between voltages reaches specified tolerance level. This method eliminates solving of simultaneous equations for load flow solution [26]. The proposed algorithm is applied on IEEE 33 bus and 69 bus systems respectively.

For IEEE 33 bus: Active power loss= 201.4762 kW

Reactive power loss= 136.6596 kVAR

For IEEE 69 bus: Active power loss= 224.9783 kW

Reactive power loss= 102.1948 kVAR

3.3 Probabilistic Power Flow (PPF) model

The solution of power flow problem (power flow model) helps to design the planning of the power system. Deterministic Power Flow model is consider snap shot scenario for a given network topology. Analytical methods are preferred for the solution of deterministic power flow problem. These methods quickly evaluate the locations and capacities for a specified set of generations and loads. But a single value does not exactly indicate the whole result because of uncertainty involved in the generations and loads. Further, in this approach, the technical issues such as voltage rise and thermal over load will not be accounted.

So for proper system planning, it is necessary to consider many load and generation conditions to assess bus voltages and line flows. Thus probabilistic power flow (PPF) model efficiently consider these uncertainties and the solution of the PPF model provides statistical moments of network output quantities. The Probabilistic Power Flow (PPF) model efficiently addresses the stochastic behavior of variables. Various methods have been proposed for evaluating power flow analysis under uncertain conditions. The Monte Carlo Simulation (MCS) gives the accurate results, which is a commonly used approach. However Point Estimate Method (PEM) is preferred, because of its less computation burden and provides identical results as that of Monte Carlo Simulation (MCS) [29-32].

3.4 PEM for solving the PPF problem

Point Estimate Method is a statistical method, which evaluates discrete points for a given continuous probability distribution curve. The point estimate method calculates the static moments of random output variables. PEM solves the probabilistic power flow model with relatively good accuracy. Rosenblueth developed the first PEM in 1975[31]. Under many PEM schemes, Hong's PEM provides the best performance [30].

The set of random output variables Z is calculated by placing each concentration of random input variable in non linear power flow equations. Z is vector of random output variables and p_i is the i^{th} random input variable. Each random variable has K concentrations.

$$Z(l,k) = F(p_1, p_2, \ldots\ldots p_{l,} \ldots\ldots\ldots\ldots p_m) \tag{3.6}$$

The function F is evaluated at $p_{l,k}$ by maintaining the mean value μ of all other remaining random variables (m-1) in (2m+1) scheme.

$$Z(l,k) = F(\mu_{p1}, \mu_{p2}, \ldots., p_{l,k}, \ldots.. \mu_{pm}) \tag{3.7}$$

$Z(l,k)$ is k^{th} concentration of l^{th} random output variable.

$P(l,k)$ is k^{th} concentration of l^{th} random input variable.

The k^{th} concentration ($p_{l,k}, w_{l,k}$) of a random variable p_l is associated with a pair of a location $p_{l,k}$ and a weight $w_{l,k}$.

The location is given by

$$p_{l,k} = \mu_{pl} + \xi_{l,k}\sigma_{pl} \tag{3.8}$$

Where μ_{pl} is the mean value of variable p_l, σ_{pl} is the standard deviation of variable p_l and

$\xi_{l,k}$ is the standard location.

The standard location $\xi_{l,k}$ and weights $w_{l,k}$ are calculated by solving the following equations.

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{\lambda_{l,4} - \frac{3}{4}(\lambda_{l,3})^2} \qquad \text{for k=1,2} \tag{3.9}$$

$$\xi_{l,3} = 0$$

The weighting factor of random input variable $p_{l,k}$ is $w_{l,k}$ associated with random output variable $Z(l,k)$.

$$\sum_{l=1}^{m}\sum_{k=1}^{K} w_{l,k} = 1 \tag{3.10}$$

$$w_{l,k} = \frac{(-1)^{3-k}}{\xi_{l,k}(\xi_{l,1}-\xi_{l,2})} \qquad \text{for k=1,2} \tag{3.11}$$

$$w_{l,3} = \frac{1}{m} - \frac{1}{\lambda_{l,4}-(\lambda_{l,3})^2}$$

$E(Z)$ is the mean value of random variable Z

$$E(Z) = \sum_{l=1}^{m}\sum_{k=1}^{K} w_{l,k} Z(l,k) \tag{3.12}$$

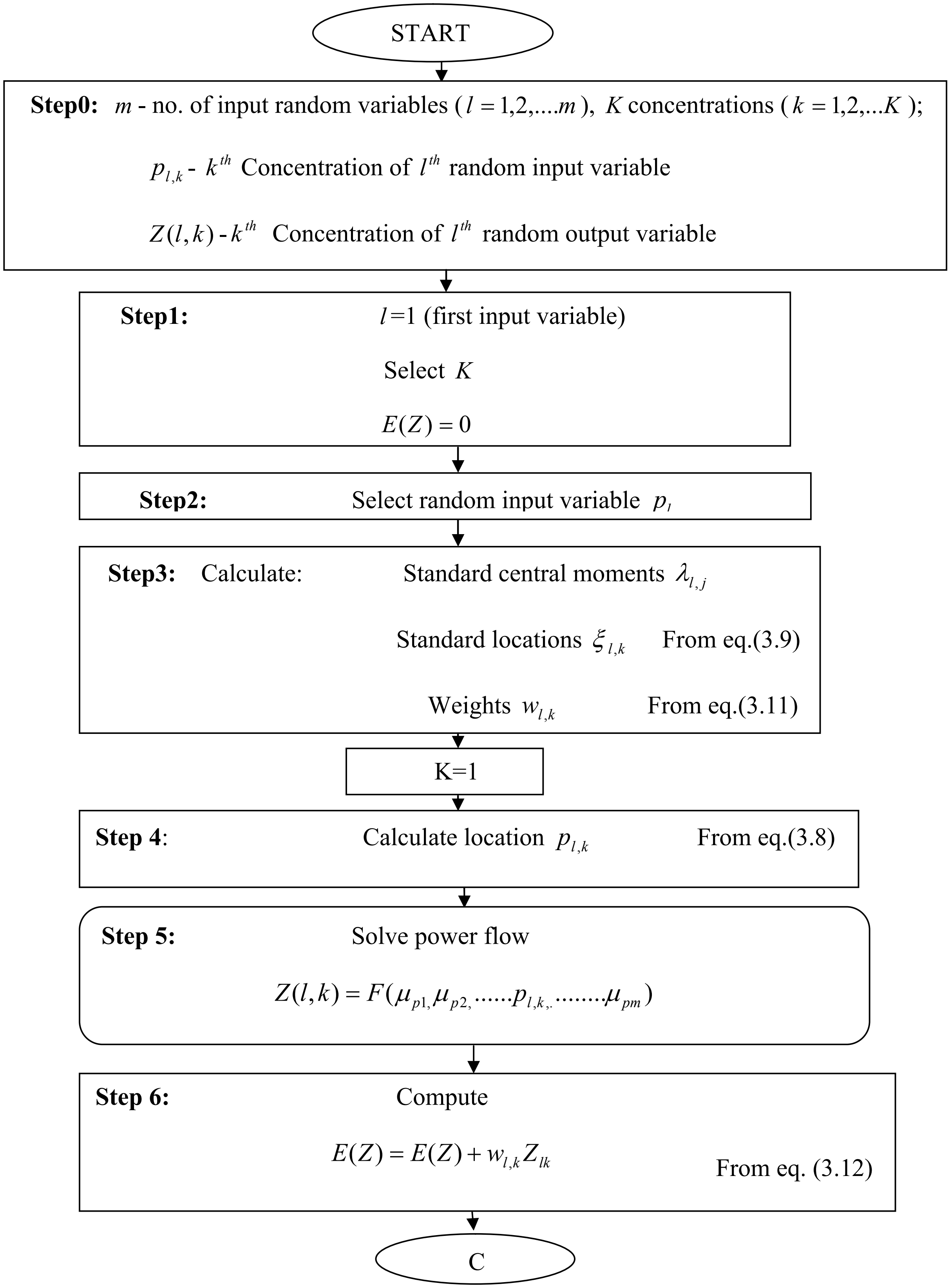
The output variable $Z(l,k)$ is taken as following terms

(i) The voltage magnitude(V) and the voltage angle (δ) of the buses

(ii) The complex power flow (S_{ij}) of the branch $i-j$ of the network

(iii) Active power loss(P_{loss})

Flowchart for solving strategy of PPF problem using PEM



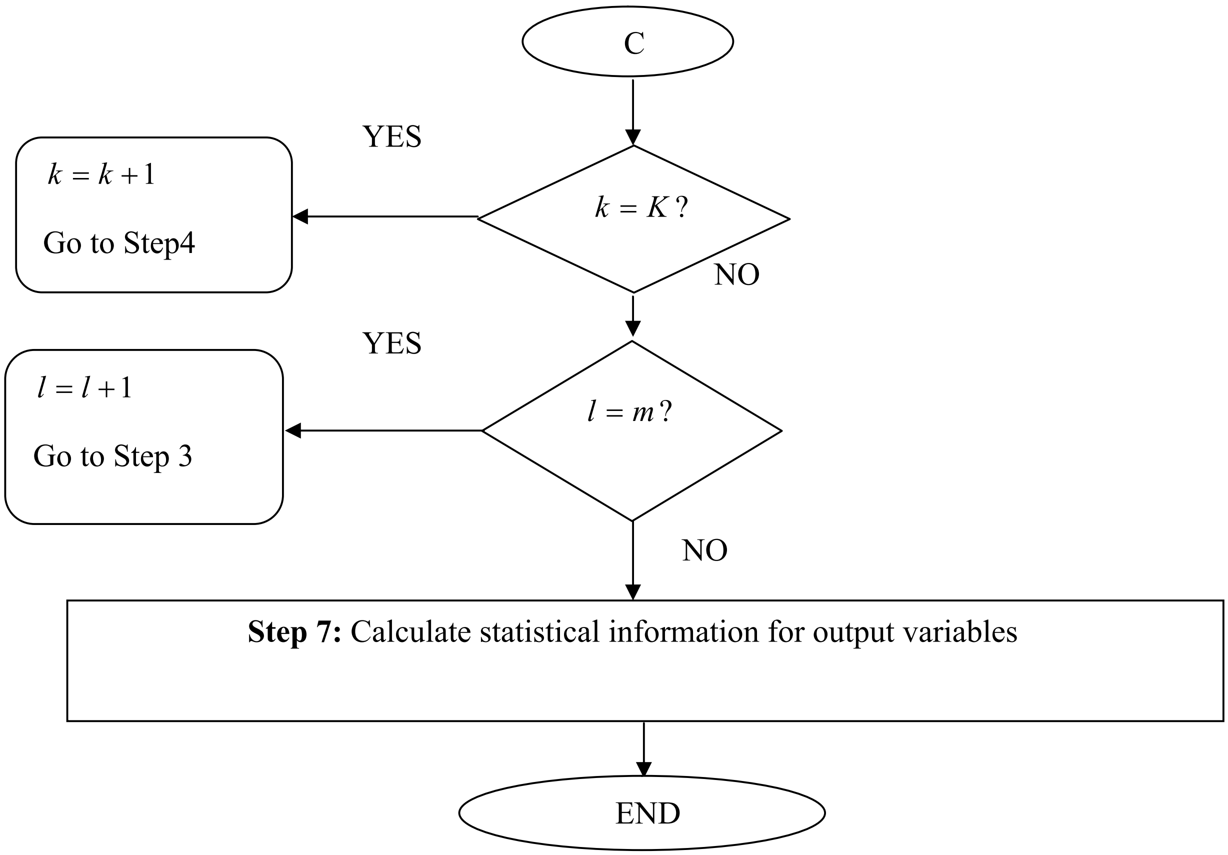


Fig. 3.3 Flow chart of the PEM for the PPF problem

CHAPTER 4

DIFFERENTIAL EVOLUTIONARY ALGORITHM

4.1 Basic Concepts of Differential Evolutionary Algorithm

Differential Evolutionary Algorithm (DEA) was proposed by “Price” and “Storn”. Differential Evolution (DE) is one of the powerful optimization under stochastic conditions. It has three operations: differential mutation, crossover, and selection. The Differential Evolution performance is better compared to other techniques in terms of its convergence speed, accuracy and robustness. Unlike evolutionary algorithms, differential evolution performs differential mutation operation for generating the distinct population [33].

The general form of DE strategy is DE/x/y/z. where x is a vector denotes either best or random vector depending on type of strategy. y denotes number of difference vectors to be taken for perturbing the vector x. z denotes either binomial or exponential crossover.

The various strategies of DE are

1) DE/rand/1/bin (classic DE)
2) DE/best/1bin
3) DE/target-to-best/1/bin
4) DE/rand/1/either-or

The steps involved in Differential Evolution (DE) are

1) Generate initial population $T_d^{i,G}$

   Target vector population is pronounced as initial population. The creation of number of vectors is determined by population size NP and the number of elements of each vector signifies the dimension of vector. Each vector/chromosome is a solution that evaluates the objective function value in multi objective optimization problem. Each element/gene of a vector is constrained by lower and upper bounds.

   The d^{th} component of i^{th} vector is given by:

$$T_d^{i,G} = b_L + \alpha * (b^U - b^L) \qquad 0 \le \alpha \le 1 \tag{4.1}$$

2) Mutation with difference vectors

The differential mutation operation is performed on the target vectors in order to obtain mutant vector. Here, the scaling factor F is chosen in the range (0,1) for generation of mutant vector. The indices r^1, r^2 and r^3 are randomly selected in the range [1, NP]. The base vector index i, and random integers r^1, r^2, r^3 are chosen as mutually exclusive integers.

$$M_d^{i,G} = T_d^{r1,G} + F * (T_d^{r2,G} - T_d^{r3,G}) \qquad i \neq r1 \neq r2 \neq r3 \qquad (4.2)$$

3) Binomial Crossover

The cross over operation enlarges the potential diversity of population after performing the differential mutation operation. The exchange of components takes place between target and mutant vectors based on cross over value in order to obtain trial vector population.

In binomial crossover, based on the comparison between random number and the value of cross over: the gene of the trial vector is inherited from either from target vector or trial vector. If CR=0, then the trial vector is resembles target vector. If CR=1, then the trial vector resembles mutant vector.

$$U_d^{i,G} = M_d^{i,G} \qquad \text{if rand()<=CR} \qquad (4.3)$$
$$T_d^{i,G}$$

4) Selection

The selection operation selects the trial vector or target vector based on its fitness value for next generation. The higher fitness value of vector yields the next generation. The trail vector will survive in the next generation for same fitness value.

$$T_d^{i,G+1} = U_d^{i,G} \qquad f(U_d^{i,G}) \leq f(T_d^{i,G}) \qquad (4.4)$$
$$T_d^{i,G}$$

4.2 Comparison of DEA versus Genetic Algorithm

The Genetic Algorithm (GA) can be applied to any type of problem that is insensitive to problem where as Differential Evolutionary Algorithm (DEA) is problem specific. In GA, operations are performed on encoded chromosomes and finally they are decoded using decoding procedure. In DEA, the Differential Evolution (DE) operators are directly performed on the actual values. The unique feature of DEA is its differential mutation operation. In mutant vector from differential mutation operation is obtained by adding a random vector to the scaled difference of two vectors. For 1-Dimentional optimization process, DE converges faster than GA and PSO due to its gradient-descent type search strategy.

4.3 Applications of Differential Evolution (DE)

It is applicable to wide variety of problems including unimodal, multimodal, separable, non-separable. The various sub areas of engineering optimization problems include electrical power systems, electromagnetism, propagation and microwave engineering, control systems and robotics, bioinformatics, chemical engineering, patter recognition and image processing, signal processing , molecular configurations, optoelectronics etc.

CHAPTER 5

OPTIMAL DG ALLOCATION USING DIFFERENTIAL EVOLUTIONARY ALGORITHM

5.1 Generation of chromosomes/vectors

Each chromosome/vector comprising of 3 part vector because of 3 types of DGs. Each part of the vector consists of locations and installed capacities of a particular type of DG. Each gene of vector is bounded by lower and upper bounds. The limits on locations are dependent on type of bus system. The installed capacities are taken in the range between 20 kW and 400 kW. Generate initially NP, D-dimensional target vector population. The mutant vector is obtained by differential mutation operation. The trial vector population is obtained by performing the cross over operation between target and mutant vectors. Based on the objective function value, target/trial vector will survive in the next iteration. The algorithm is terminated by giving maximum iteration condition. Select the overall best vector found in the solving procedure.

5.2 Evaluation of fitness function and handling of constraints

Using point estimate method (PEM), extracting k concentrations from each installed capacity in a vector. Run the deterministic load flow by keeping one concentration at a time while replacing the other capacities corresponding to their mean values. Finally one more evaluation is performed by replacing all the capacities with their mean values. The resultant output quantities such as voltage and angle of bus, power loss, active and reactive power flow, active and reactive power injection are obtained by weighted sum of objective function when considering one concentration at a time. The fitness function calculated for each vector. Fitness function is the summation of objective function value and penalty function. The penalty term added to objective function in case of constraints violation.

$$F_{fitness} = \overline{f}(X,\xi) + \sum_{i=1}^{N_{constraints}} penalty_i \tag{5.1}$$

Where $\overline{f}(X,\xi)$ denotes the objective function value without penalty. The set of constraints is denoted as $N_{constraints}$. For violation of i^{th} constraint, $penalty_i$ is added to objective function. The formula for penalty is given as

$$penalty_i = e_i y_i^r \tag{5.2}$$

Where y_i denotes distance either from the upper or the lower bound, in the case of constraint violation. e_i is the coefficient of violation. r is taken as two [35].

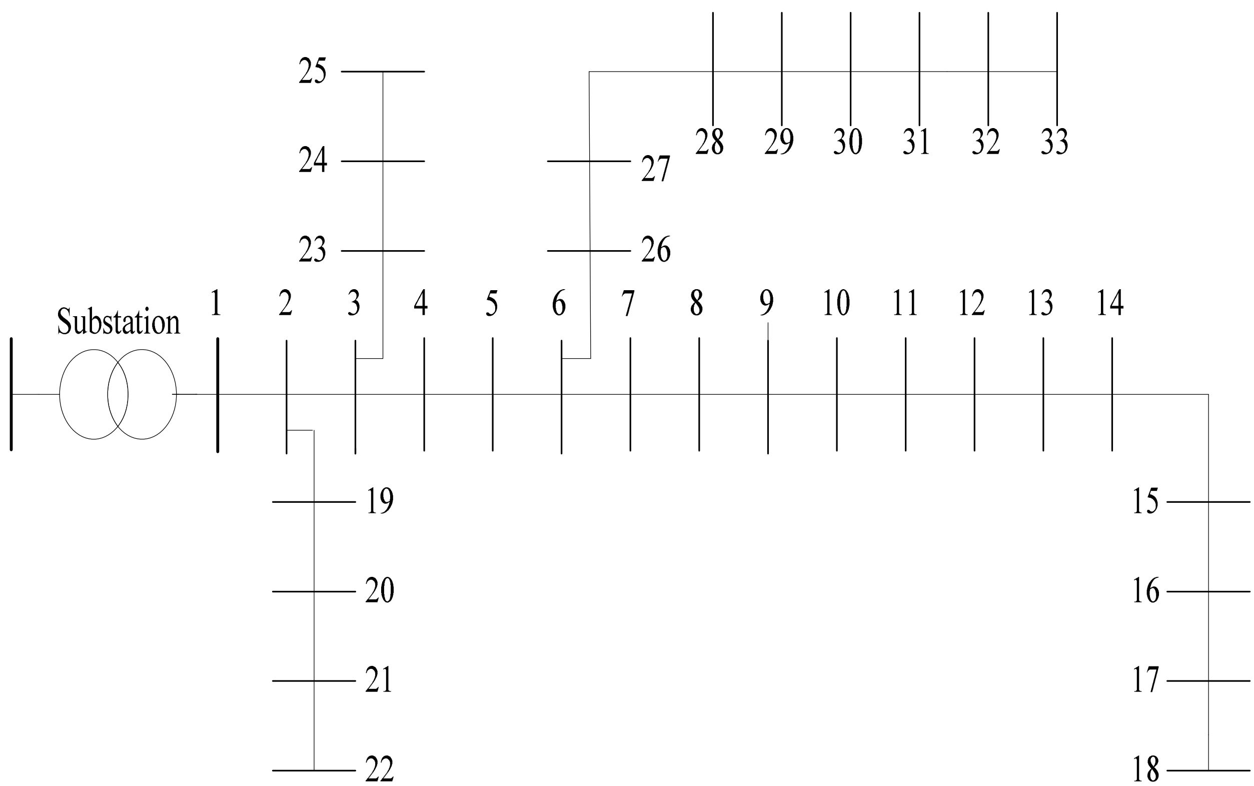


Fig. 5.1 IEEE 33-bus radial distribution system

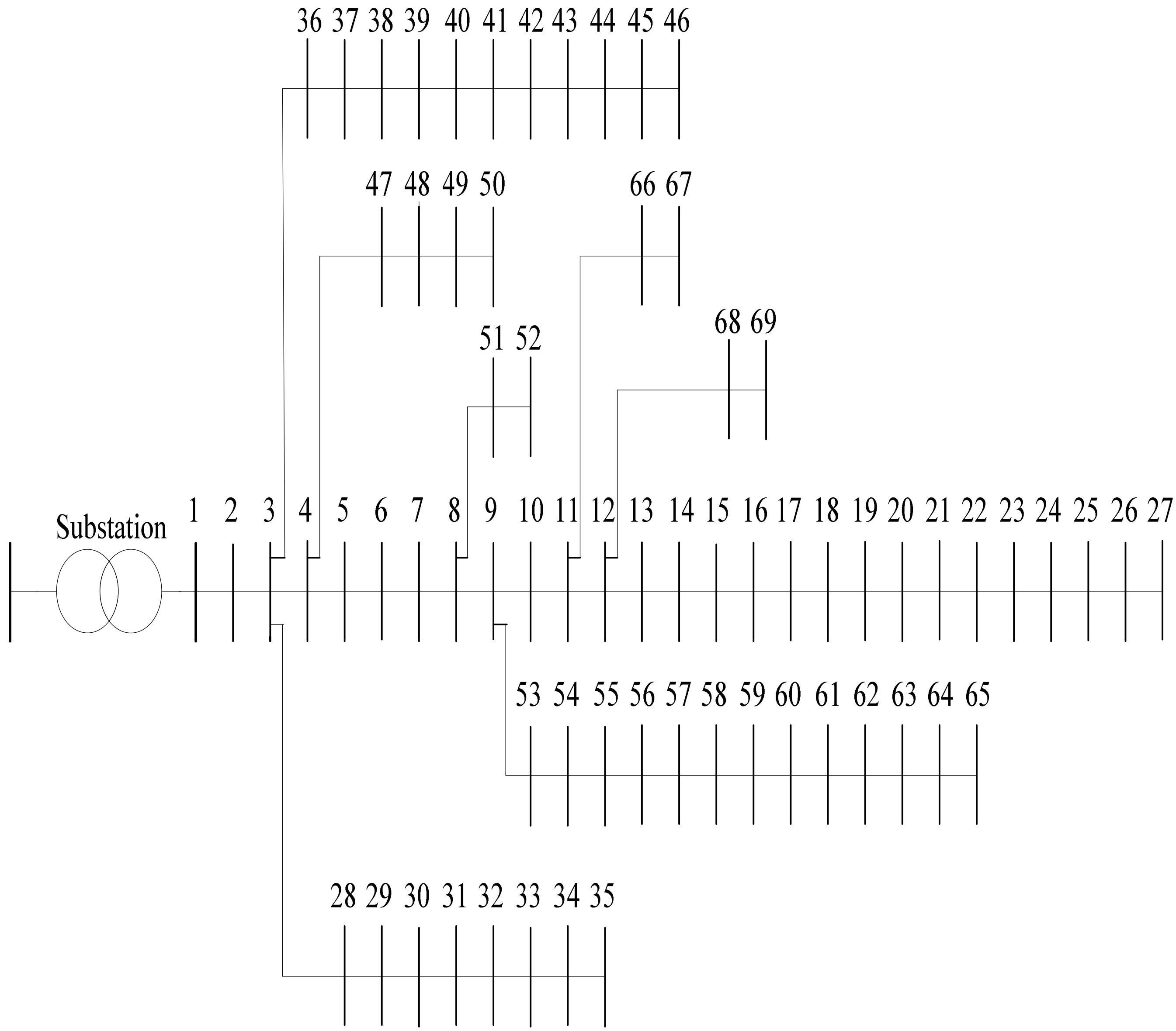


Fig. 5.2 IEEE 69-bus radial distribution system

Flowchart of the proposed DEA-PEM method

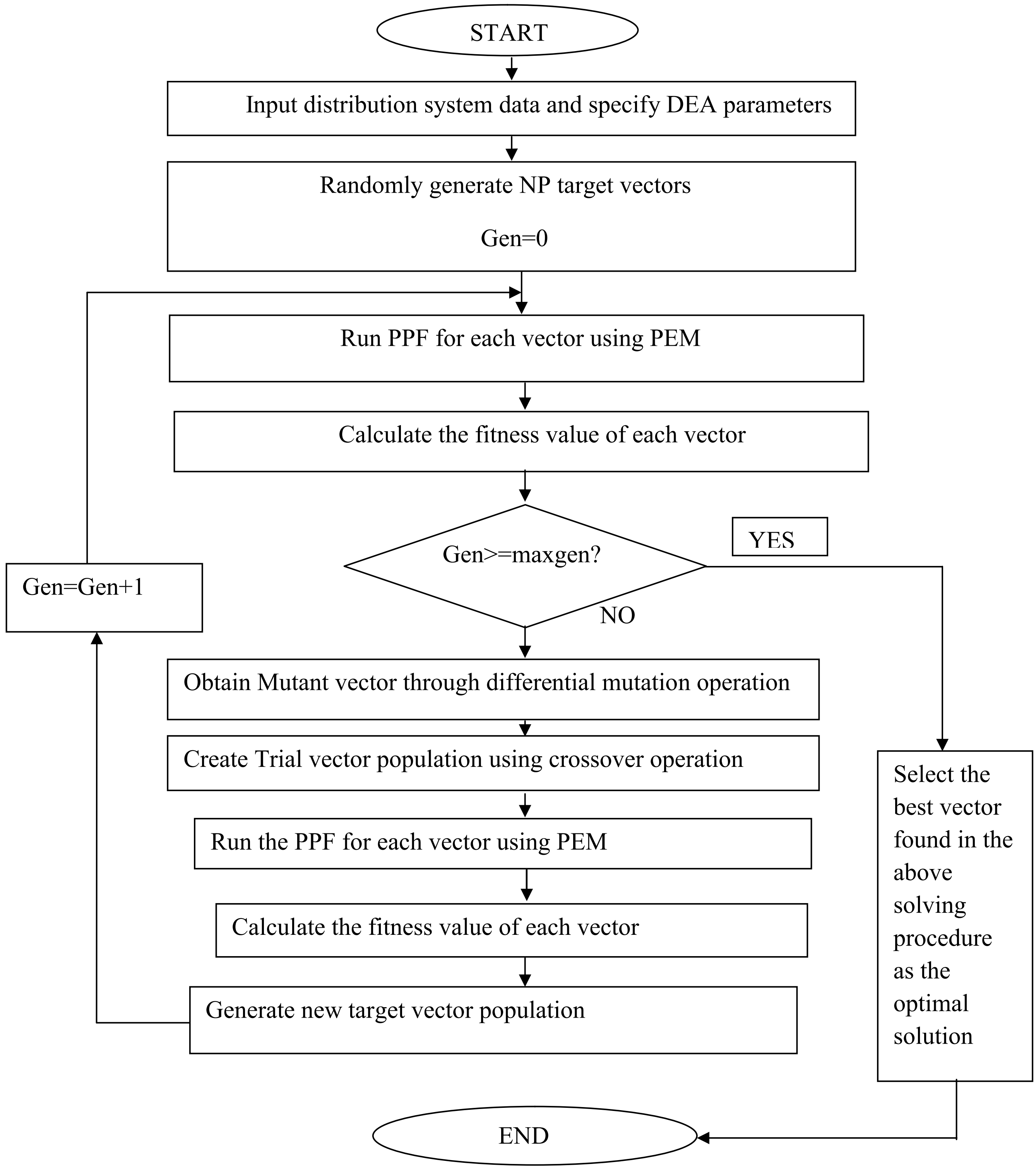


Fig. 5.3 The proposed DEA-PEM approach

CHAPTER 6

SIMULATION RESULTS AND DISCUSSIONS

6.1 IEEE 33-BUS SYSTEM

33-bus system without and with DG

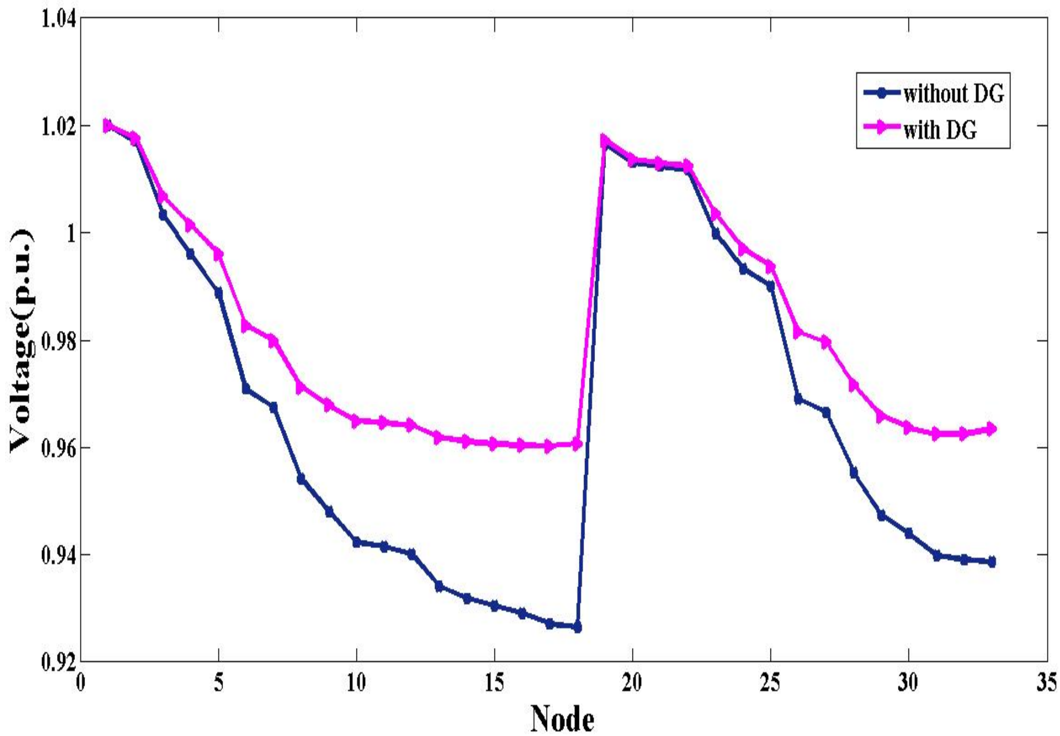


Fig. 6.1 Voltage variation at each node before and after DG placement

7	23	33	14	18	2	33	33	20	40	400	400	400	400	20	20

← LOCATIONS → ← CAPACITY (kW) →

The voltage at end node is improved from 0.9388 p.u. to 0.9634 p.u. after optimally allocating the distributed generators. .

<u>33-bus system with DG</u>

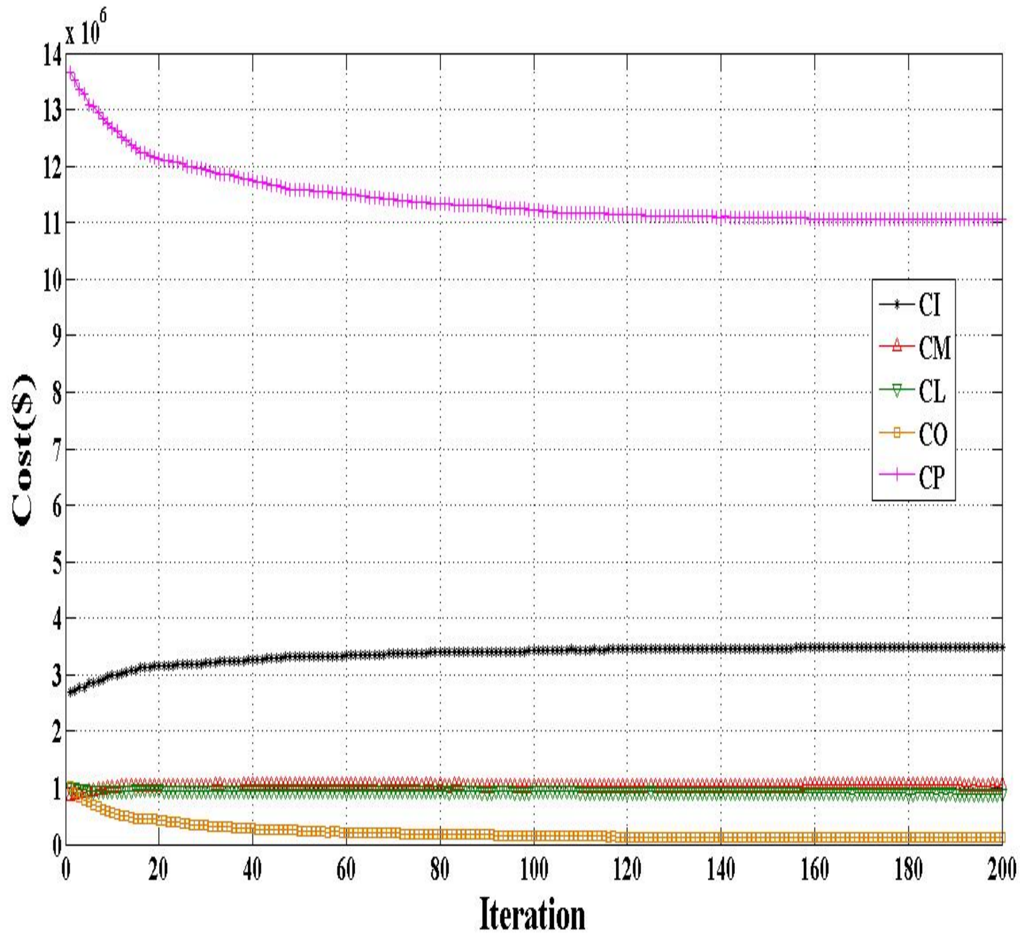


Fig. 6.2 Evaluation of individual costs of the best chromosome per iteration of the DEA

For 25 years of planning period the total cost for distributed network operation including distributed generation is less compared to without distributed generation.

33-bus system with DG

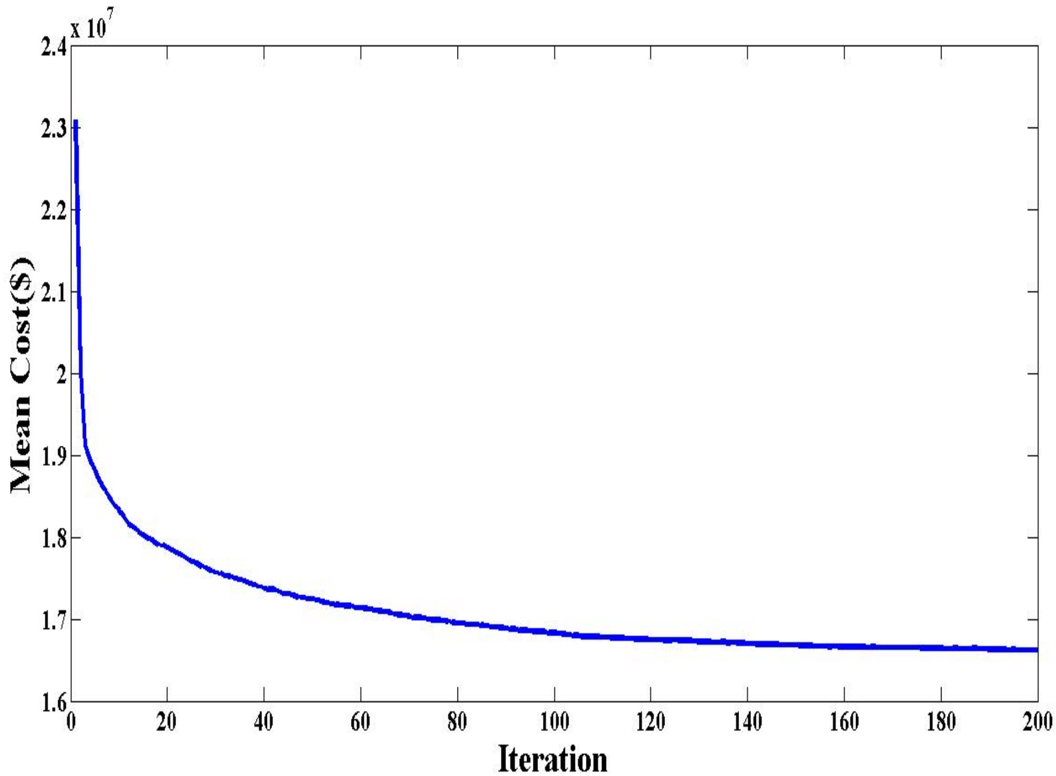


Fig. 6.3 Mean cost curve of the best chromosome per iteration of the DEA

The mean value of fitness function is plotted for every iteration. The fitness function is mainly influenced by energy purchased cost due to its large value. The decrease in energy purchased cost results in increase of DG investment cost. However, the mean cost curve decreases with increase in iteration. The penalties are added to objective function value in case of violation of constraints. The constraints include voltage limit thermal limit and DG penetration limit. The total DG penetration limit is obtained as almost 50% of load (1850kW) and the renewable distributed generation capacity is obtained a huge percent of total DG capacity. The value of penalty coefficients for voltage and thermal limit are considered in the order of 10^8. In case of distribution generation capacity, the penalty coefficient is taken in the order of 10^3.

Table 6.1 Cost before DG placement for 33-bus system

Voltage at end node	0.9388 p.u.
Energy loss cost	1.4218×10^6\$
Energy purchased cost	19.6752×10^6\$
Total cost	21.097×10^6\$

Table 6.2 Cost after DG placement for 33-bus system

DG investment cost	3.48×10^6\$
DG maintenance cost	1.06×10^6\$
DG operating cost	0.12×10^6\$
Network loss cost	0.89×10^6\$
Cost of purchased energy	11.05×10^6\$
Total cost	16.45×10^6\$

6.2 IEEE 69-BUS SYSTEM

<u>69-bus system without and with DG</u>

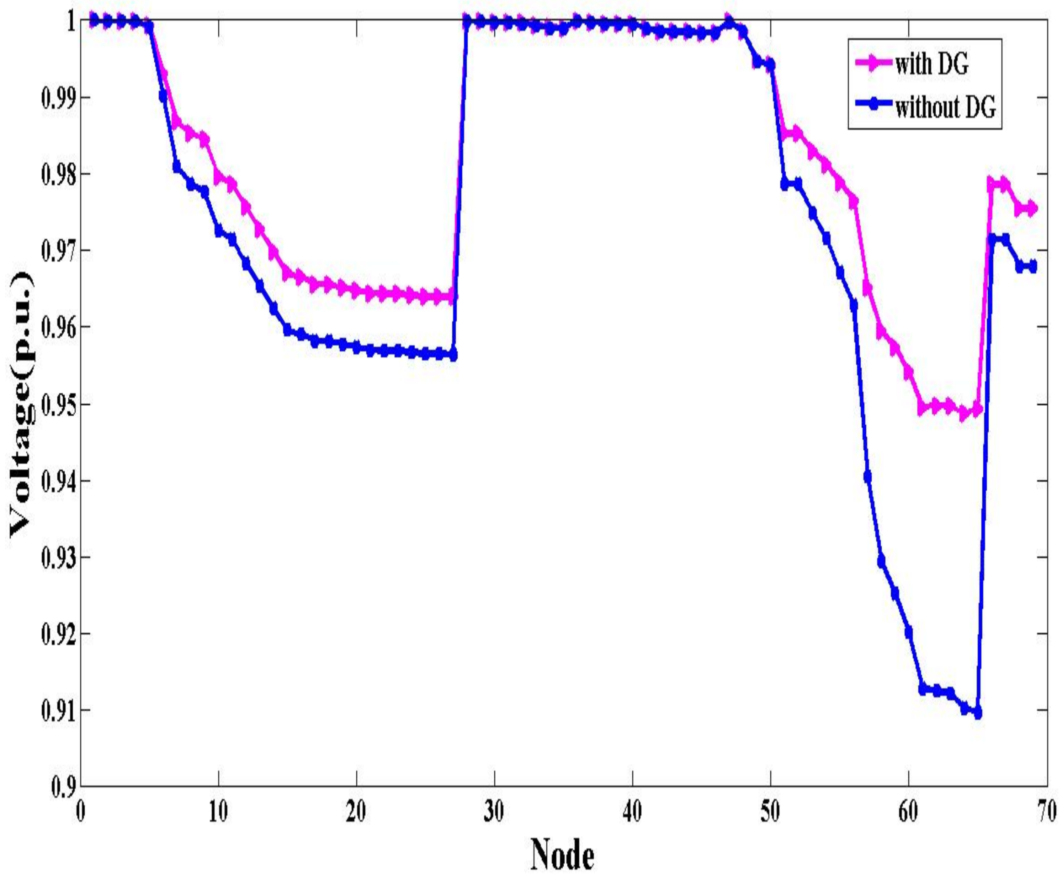


Fig. 6.4 Voltage variation at each node before and after DG placement

62	69	69	65	63	4	14	18	280	160	220	400	400	400	20	20

← LOCATONS → ← CAPACITY (kW) →

The voltage at end node is improved from 0.9680 p.u. to 0.9754 p.u. after optimally allocating the distributed generators.

69-bus system with DG

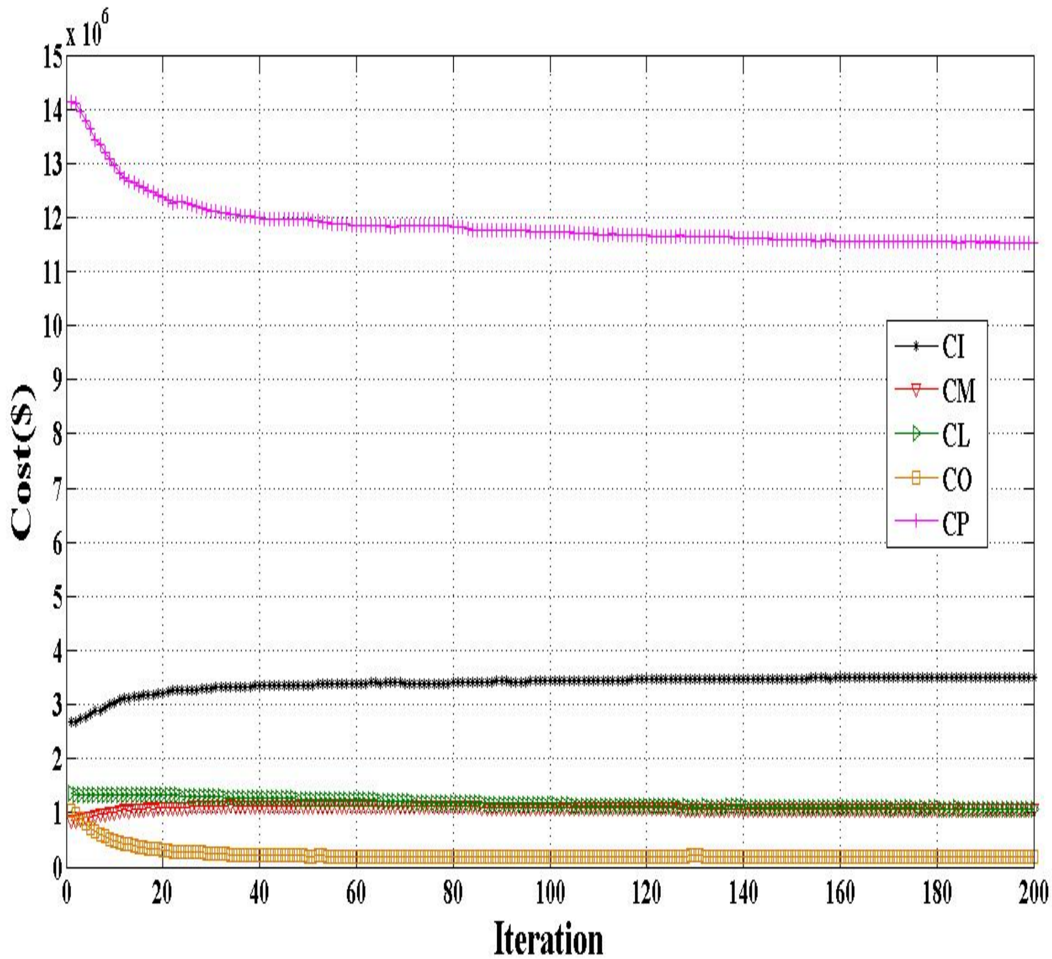


Fig. 6.5 Evaluation of individual costs of the best chromosome per iteration of the DEA

For 25 years of planning period the total cost for distributed network operation including distributed generation is less compared to without distributed generation.

69-bus system with DG

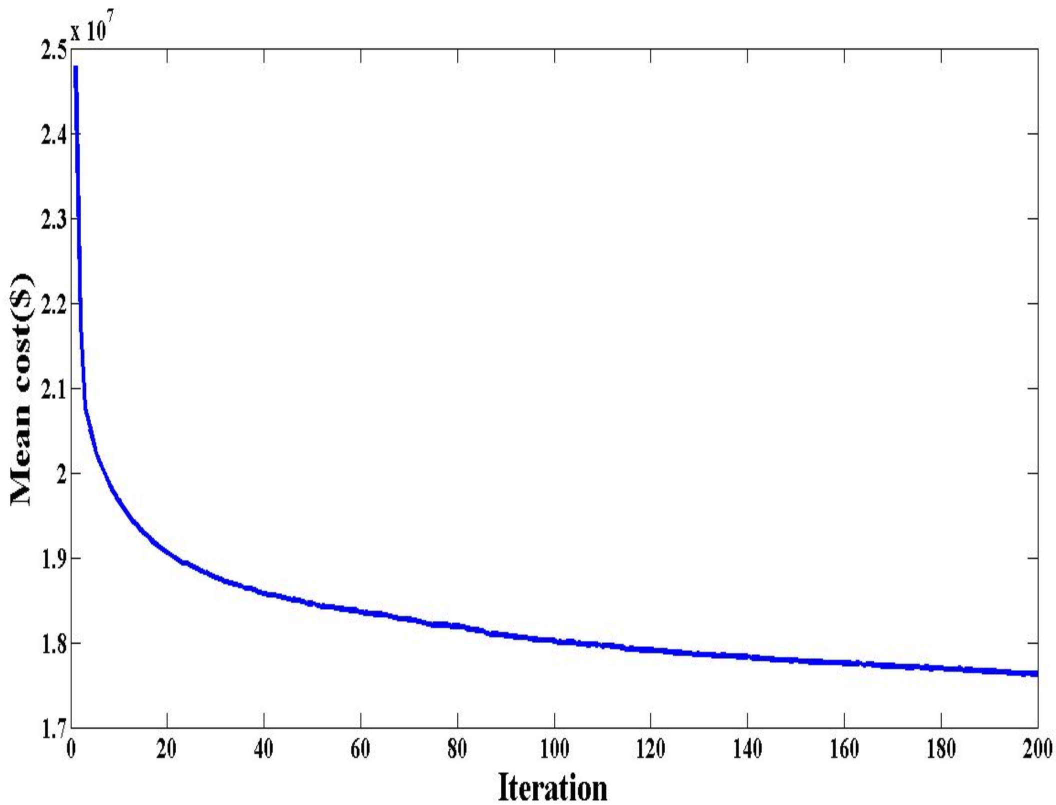


Fig. 6.6 Mean cost curve of the best chromosome per iteration of the DEA

The mean value of fitness function is plotted for every iteration. The fitness function is mainly influenced by energy purchased cost due to its large value. The decrease in energy purchased cost results in increase of DG investment cost. However, the mean cost curve decreases with increase in iteration. The penalties are added to objective function value in case of violation of constraints. The constraints include voltage limit thermal limit and DG penetration limit. The total DG penetration limit is obtained as almost 50% of load (1900kW) and the renewable distributed generation capacity is obtained a huge percent of total DG capacity. The value of penalty coefficients for voltage and thermal limit are considered in the order of 10^8. In case of distribution generation capacity, the penalty coefficient is taken in the order of 10^3.

Table 6.3 Cost before DG placement for 69-bus system

Voltage at end node	0.9680 p.u.
Energy loss cost	1.588×10^6\$
Energy purchased cost	20.14×10^6\$
Total cost	21.73×10^6\$

Table 6.4 Cost after DG placement for 69-bus system

DG investment cost	3.5×10^6\$
DG maintenance cost	1.14×10^6\$
DG operating cost	0.19×10^6\$
Network loss cost	1.06×10^6\$
Cost of purchased energy	11.53×10^6\$
Total cost	17.18×10^6\$

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

It is observed that with the optimal placement of distributed generators in distribution networks improves the voltage profile, reduce the network losses and also reduce carbon emissions by considering network constraints and DG operation constraints. The proposed method is applied on IEEE 33 bus and IEEE 69 bus systems respectively. Here, the multi objective planning program considers the optimization of various costs. For 33 bus system, the total cost is reduced from $21.1\times10^{6}\$$ to $16.45\times10^{6}\$$ with proper allocation of distributed generation. For 69 bus system, the total cost is reduced from $21.73\times10^{6}\$$ to $17.18\times10^{6}\$$ with proper allocation of distributed generators. In addition to that voltage profile is improved and reduction in carbon emission due to sufficient amount of renewable penetration. It is observed that the decrement in cost of energy purchased from grid would cause increment in investment and maintenance cost due to its major portion in total cost.

7.2 Future Scope

The work is done on the basis of weighted sum of multi objective planning problem. Multi objective planning problem is always having conflicting objectives. The maximization of distributed generation capacity conflicts with decrement in line losses. The investment cost minimization conflicts with both capacity maximization and line losses. Thus, multi objective planning problem have set of solutions rather than single solution. The set of solutions is known as pareto set, in which all objectives optimized simultaneously. The future work is multi objective planning problem based on pareto approach.

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APPENDIX -A

Table A.1 Data for IEEE 33-bus distribution system

Branch	Sending bus	Receiving bus	Resistance R, Ω	Reactance X, Ω	Real power load at receiving bus, MW	Reactive power load at receiving bus, Mvar
1	1	2	0.0922	0.0477	0.1	0.06
2	2	3	0.493	0.2511	0.09	0.04
3	3	4	0.366	0.1864	0.12	0.08
4	4	5	0.3811	0.1941	0.06	0.03
5	5	6	0.819	0.707	0.06	0.02
6	6	7	0.1872	0.6188	0.2	0.1
7	7	8	1.7114	1.2351	0.2	0.1
8	8	9	1.03	0.74	0.06	0.02
9	9	10	1.04	0.74	0.06	0.02
10	10	11	0.1966	0.065	0.045	0.03
11	11	12	0.3744	0.1238	0.06	0.035
12	12	13	1.468	1.155	0.06	0.035
13	13	14	0.5416	0.7129	0.12	0.08
14	14	15	0.591	0.526	0.06	0.01
15	15	16	0.7463	0.545	0.06	0.02
16	16	17	1.289	1.721	0.06	0.02
17	17	18	0.732	0.574	0.09	0.04
18	2	19	0.164	0.1565	0.09	0.04
19	19	20	1.5042	1.3554	0.09	0.04
20	20	21	0.4095	0.4784	0.09	0.04
21	21	22	0.7089	0.9373	0.09	0.04
22	3	23	0.4512	0.3083	0.09	0.05
23	23	24	0.898	0.7091	0.42	0.2
24	24	25	0.896	0.7011	0.42	0.2
25	6	26	0.203	0.1034	0.06	0.025
26	26	27	0.2842	0.1447	0.06	0.025
27	27	28	1.059	0.9337	0.06	0.02
28	28	29	0.8042	0.7006	0.12	0.07
29	29	30	0.5075	0.2585	0.2	0.6
30	30	31	0.9744	0.963	0.15	0.07
31	31	32	0.3105	0.3619	0.21	0.1
32	32	33	0.341	0.5302	0.06	0.04

Table A.2 Average value (μ) and standard deviation (σ) of load growth for the IEEE 33-bus distribution system

Bus	μ (kW)	σ (kW)
1	0	0
2	0.0035	0.0013
3	0.00315	0.0018
4	0.0042	0.0018
5	0.0021	0.0012
6	0.0021	0.00085
7	0.007	0.0031
8	0.007	0.00327
9	0.0021	0.00096
10	0.0021	0.00125
11	0.001575	0.00061
12	0.0021	0.0012
13	0.0021	0.00082
14	0.0042	0.0025
15	0.0021	0.00071
16	0.0021	0.00073
17	0.0021	0.00113
18	0.00315	0.0011
19	0.00315	0.0015
20	0.00315	0.0014
21	0.00315	0.00123
22	0.00315	0.00138
23	0.00315	0.00149
24	0.0147	0.0046
25	0.0147	0.0078
26	0.0021	0.0012
27	0.0021	0.00084
28	0.0021	0.00112
29	0.0042	0.00218
30	0.007	0.0037
31	0.00525	0.0022
32	0.00735	0.0036
33	0.0021	0.00084

Table A.3 Data for IEEE 69-bus distribution system

Branch	Sending bus	Receiving bus	Resistance R, Ω	Reactance X, Ω	Real power load at receiving bus, kW	Reactive power load at receiving bus, kvar
1	1	2	0.0005	0.0012	0	0
2	2	3	0.0005	0.0012	0	0
3	3	4	0.0015	0.0036	0	0
4	4	5	0.0251	0.0294	0	0
5	5	6	0.366	0.1864	2.6	2.2
6	6	7	0.3811	0.1941	40.4	30
7	7	8	0.0922	0.047	75	54
8	8	9	0.0493	0.0251	30	22
9	9	10	0.819	0.2707	28	19
10	10	11	0.1872	0.0691	145	104
11	11	12	0.7114	0.2351	145	104
12	12	13	1.03	0.34	8	5.5
13	13	14	1.044	0.345	8	5.5
14	14	15	1.058	0.3496	0	0
15	15	16	0.1966	0.065	45.5	30
16	16	17	0.3744	0.1238	60	35
17	17	18	0.0047	0.0016	60	35
18	18	19	0.3276	0.1083	0	0
19	19	20	0.2106	0.0696	1	0.6
20	20	21	0.3416	0.1129	114	81
21	21	22	0.014	0.0046	5.3	3.5
22	22	23	0.1591	0.0526	0	0
23	23	24	0.3463	0.1145	28	20
24	24	25	0.7488	0.2745	0	0
25	25	26	0.3089	0.1021	14	10
26	26	27	0.1732	0.0572	14	10
27	3	28	0.0044	0.0108	26	18.6
28	28	29	0.064	0.1565	26	18.6
29	29	30	0.3978	0.1315	0	0
30	30	31	0.0702	0.0232	0	0
31	31	32	0.351	0.116	0	0
32	32	33	0.839	0.2816	14	10
33	33	34	1.708	0.5646	19.5	14
34	34	35	1.474	0.4873	6	4
35	3	36	0.0044	0.0108	26	18.55
36	36	37	0.064	0.1565	26	18.55
37	37	38	0.1053	0.123	0	0
38	38	39	0.0304	0.0355	24	17
39	39	40	0.0018	0.0021	24	17
40	40	41	0.7283	0.8509	1.2	1
41	41	42	0.31	0.3623	0	0

42	42	43	0.041	0.0478	6	4.3
43	43	44	0.0092	0.0116	0	0
44	44	45	0.1089	0.1373	39.22	26.3
45	45	46	0.0009	0.0012	39.22	26.3
46	4	47	0.0034	0.0084	0	0
47	47	48	0.0851	0.2083	79	56.4
48	48	49	0.2898	0.7091	384.7	274.5
49	49	50	0.0822	0.2011	384.7	274.5
50	8	51	0.0928	0.0473	40.5	28.3
51	51	52	0.3319	0.1114	3.6	2.7
52	9	53	0.174	0.0886	4.35	3.5
53	53	54	0.203	0.1034	26.4	19
54	54	55	0.2842	0.1447	24	17.2
55	55	56	0.2813	0.1433	0	0
56	56	57	1.59	0.5337	0	0
57	57	58	0.7837	0.263	0	0
58	58	59	0.3042	0.1006	100	72
59	59	60	0.3861	0.1172	0	0
60	60	61	0.5075	0.2585	1244	888
61	61	62	0.0974	0.0496	32	23
62	62	63	0.145	0.0738	0	0
63	63	64	0.7105	0.3619	227	162
64	64	65	1.041	0.5302	59	42
65	11	66	0.2012	0.0611	18	13
66	66	67	0.0047	0.0014	18	13
67	12	68	0.7394	0.2444	28	20
68	68	69	0.0047	0.0016	28	20

APPENDIX-B

Table B.1 Investment, maintenance and operating costs of DGs and energy loss cost of the distribution system

Cost component	DG type		
	Wind DG	Photovoltaics DG	Fueled DG
Investment cost C^I, $/kW	1800	2000	850
Maintenance cost C^M, $/kWh	0.05	0.03	0.02
Operating cost C^O, $/kWh	0	0	0.02
Energy loss cost C^L, $/kWh	0.08	0.08	0.08

Table B.2 Technical specifications of DGs

DG type	Technical Specifications
Wind turbines	V_{ci} = 4 m/s V_n = 15 m/s V_{co} = 25 m/s Power factor = 0.9 lagging
Photovoltaic's	S_n = 1000 W/m^2 *power* factor = 1.0
fueled DGs	*stable* power power factor = 0.9 lagging

Table B.3 Maintenance and operating hours of DG

DG type	Maintenance hours	Operating hours
Wind Turbines	2160	3500
Photovoltaic's	1350	2400
Fueled DGs	360	8260